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*Supply constraints and waitlists in new product diffusion*

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## Supply Constraints and Waitlists in New Product Diffusion

Constraints on production capacity adjustment present a strategic and operational problem for managers launching products when demand is uncertain. Stock-outs can be costly if demand exceeds available product supply, as sales are deferred or lost when prospective customers are waitlisted. Recent research on diffusion under supply constraints has analyzed launch strategies to minimize the chance of stock-outs. Others suggest that waitlisted buyers generate social exposure that can boost customer demand and shape the diffusion process. We develop a generalized model of new product diffusion under supply constraints that explicitly accounts for endogenous customer waitlisting and waitlist-generated word-of-mouth. We estimate the model for a prominent example of waitlisting, the launch of the Toyota Prius hybrid-electric vehicle in the United States, finding evidence of positive word-of-mouth from waitlisted buyers. Inclusion of endogenous supply constraints and waitlisting also alters the estimated contribution of marketing and adopter word-of-mouth.

Keywords: new product diffusion; waitlists; supply constraints; hybrid electric vehicles

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## Introduction

Manufacturers launching new products face a difficult challenge: providing sufficient production capacity to match supply with often highly uncertain demand, while capacity lead times are substantial and adjustment costs high. Firms must forecast far ahead to ensure they have sufficient capacity to satisfy demand while avoiding costly excess capacity, inventories and holding costs.

The problem of how to deal with uncertain demand when introducing new products has been addressed in a variety of ways across academic disciplines. Marketing diffusion models focus on generating effective demand forecasts for new products, many building on the classic Bass diffusion model (Bass 1969) (for detailed reviews of this literature see Mahajan et al. (1990), Geroski (2000) and Peres et al. (2010)). However, the marketing literature mostly does not account for endogenous capacity acquisition and the possibility of inadequate or excess capacity, implicitly assuming that that capacity can be adjusted quickly to meet demand or, if capacity acquisition takes time, that demand forecasts are nearly perfect so that imbalances that might affect product availability or prices never arise. Neither assumption is typically correct (Sberman et al. 2007).

The operations management literature, in contrast, stresses the importance of flexibility in capacity planning to enable firms to respond to uncertainty in future demand (for example Fine and Freund (1990), Gupta et al. (1992), Li and Tirupati (1995), Graves and Tomlin (2003), Goyal and Netessine (2007), Jayswal et al. (2011)). More recently, researchers at the marketing-

operations interface have worked to integrate these perspectives, exploring the interaction of supply and demand in the presence of supply constraints. For example, authors including Ho et al. (2002), Kumar and Swimanathan (2003) and Shen et al. (2011) develop optimal inventory management strategies in the presence of supply constraints to minimize the likelihood of costly inventory shortages, emphasizing the potential for prospective buyers to be lost as a result of being forced to wait (Larson 1987). Amini et al. (2012) develop an agent-based diffusion model with supply constraints, finding that negative word-of-mouth from dissatisfied consumers has a significant impact on optimal production policies.

Scholars in the system dynamics tradition have long stressed the importance of interactions between product availability and demand, beginning with Forrester's first supply chain model (Forrester 1961). Forrester included explicit backlogs throughout his supply chain model, implying customers in every echelon waited for delivery after placing orders. Low product availability has two impacts on demand. First, as delivery delay for a product rises, customers throughout a supply chain must increase the supply line of product on order. Second, over the longer term, long delivery delays reduce product attractiveness, causing customers to seek alternate sources of supply. Forrester's famous "Market Growth" model (Forrester 1968) developed the latter theme, showing how inadequate capacity can slow or even reverse sales growth even when the potential market for a firm's product is unlimited. Milling (1996) and Maier (1998) develop system dynamics models of new product development and diffusion that consider the negative effect of low availability on adoption and diffusion, applying

their models to pricing and substitution across product generations (see Milling (2002) for an overview). Paich and Sterman (1993) provide a new product diffusion model with explicit interactions between customer demand and capacity acquisition lags, showing through an experimental study how common decision rules used by participants lead to significant capacity overshoots and subsequent firm losses.

While these works make important theoretical contributions to the management of new product launch under supply constraints, prior research ignores how the presence of waitlists may influence the diffusion process, particularly the possibility that shortages and waitlists might be beneficial by stimulating interest in new products. Waitlists have been repeatedly observed in new product launches, including Apple's iPad tablet computer (AppleInsider 2010), Sony's Playstation 3 game console (Sabbagh 2006), Harley-Davidson motorcycles (Peak 1993) and Toyota's Prius hybrid-electric vehicle (Automotive News 2004). The prevalence of long waitlists is surprising if the effect of supply constraints is as negative as the existing literature suggests. One possibility is that firms may be unwilling to implement strategies such as inventory stockpiling and dynamic pricing that would prevent the emergence and persistence of waitlists. Alternatively, waitlists may in some cases provide benefits such as status for waitlisted buyers and social proof about the value of the product that stimulates additional demand (Debo and van Ryzin 2009). Understanding the conditions under which waitlists help and hinder diffusion is critical if firms are to effectively leverage strategic scarcity as a tool for new product launch.

In this paper we develop a model of new product diffusion with supply constraints and endogenous customer waitlists to explore the effect of waitlists on diffusion. We capture social exposure from advertising and word-of-mouth arising from the installed base of adopters, both central in Bass-like models, but also the possibility of social exposure from waitlisted buyers (as first proposed by Jain et al. 1991), the valence of which may be negative (because waiting may be frustrating and costly) or positive (signaling the value of the product). We test the model empirically using a leading example of waitlisting, the launch of the Toyota Prius hybrid-electric vehicle (HEV) in the United States. Because data on waitlists are often difficult to obtain, and not recorded in the same systems that track sales, we compile a unique dataset to estimate the length of Prius waitlists from multiple sources, which reveals multiple periods of lengthy waitlists interspersed with periods of surplus inventory. We test our model against comparable models that ignore supply constraints and waitlists, finding that capturing supply constraints endogenously explains the origins of lengthy and persistent waitlists, and significantly improves model explanatory power. We also find that waitlisted Prius buyers generate positive social exposure, which we attribute to waitlists attracting media attention and generating hype.

The contributions of our research are threefold. First, we demonstrate that diffusion models omitting supply constraints and waitlists yield biased estimates of the relative importance of advertising and social exposure, affecting the efficacy of policy levers available to firms launching new products. Second, by modeling the interactions between supply constraints and waitlists, we identify conditions in which waitlisting can be an effective strategic tool during new

product launch. Third, our analysis, in showing how effective estimation depends on both model structure and access to appropriate data, reflects more generally on the value of leveraging intermediate-level data that captures the variables of greatest concern to decision-makers (Homer 2012, 2014).

## **The Dynamics of Supply and Demand in New Product Diffusion**

Mismatches between supply and demand are ever-present in durable goods markets, because consumer demand can be volatile and difficult to forecast, while lengthy time delays and significant costs govern adjustments in production capacity. For example, expansion of manufacturing facilities can take years, requiring managers to perceive the need for additional capacity, receive necessary organizational and regulatory approvals, construct plant and equipment, and hire and train new staff. Mismatches between supply and demand in both directions can be costly. When demand exceeds supply, sales are necessarily delayed, and may be lost if a customer chooses to buy a competitor's product (Urban et al. 1990). When supply exceeds demand, firms may incur inventory holding costs, discounting and/or obsolescence of inventory.

Waitlists are a commonly observed phenomenon during new product introduction, providing evidence that customer demand exceeds the available product supply. However, waitlists can only persist if customers are willing to wait and if firms are unwilling to raise prices sufficiently to clear the market. Why might firms not raise prices given surplus demand? Possible explanations include menu costs associated with price changes (e.g., Sheshinski and

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Weiss 1977, Akerlof and Yellen 1985), the potential for accusations of price gouging, or the unfairness ('transaction disutility') that customers may feel if they are charged more than they were expecting (Thaler 1985, Bolton et al. 2003). And why are consumers willing to wait? Consumers may be unwilling to switch because no suitable alternative exists, because of the product's status signaling potential, for example, the commitment to environmental stewardship that is widely attributed to Toyota Prius drivers (Heffner et al. 2007; Turrentine and Kurani 2007), or because of network externalities that make a particular product more attractive due to its compatible installed base (Katz and Shapiro 1985, Arthur 1989).

Supply constraints and waitlists influence the process of innovation diffusion in two distinct ways. First, supply constraints by definition place a ceiling on the rate of new product adoptions, slowing the accumulation of the installed base of adopters and therefore the rate at which social exposure and word-of-mouth create further demand. Here the firm incurs costs as sales are delayed or lost to competitors, as well as waitlist maintenance costs. Often such stock-outs are unintentional, although Kumar and Swaminathan (2003) suggest that it could be optimal for firms to strategically withhold inventory and avoid sales in order to control demand growth. Second, waitlists may generate social exposure that influences future demand for the product, positively or negatively. Waitlists may have a positive influence on demand, providing social proof of the product's desirability to consumers who are uncertain (Cialdini 2007), and highlighting scarcity that can make products more attractive to consumers (Bikhchandani et al. 1998). In such cases, firms may benefit from strategically inducing waitlists to generate



additional demand. Alternatively, the frustration associated with being made to wait may generate negative word-of-mouth, consistent with classical queuing theory (Larson 1987). The strength and valence of social exposure generated by waitlisted buyers is therefore an empirical question.

Finally, to quantify how waitlists influence the trajectory of new product diffusion, it is critical to capture the length of waitlists explicitly, rather than relying on inventory coverage, which, because coverage data are more readily available, has been commonly used as a supply-side measure of product scarcity (e.g. Balachander et al. 2009; Cachon and Olivares 2010). Inventory coverage, while often used as a proxy, is not a sufficient statistic for waitlist length, because inventory coverage cannot fall below zero. When the non-negativity constraint is binding, the waitlist cannot be inferred from coverage data; it could be moderate or very large, and could be growing or shrinking (see Supplementary Information for a formal proof). That information, as we show below, is important in quantifying the extent of excess customer demand and effectively estimating the relative strength of different social exposure channels.

## **Model Formulation**

Our model explicitly distinguishes social exposure from consideration (Struben and Sterman 2008) to capture consumer learning about product attributes over time prior to adoption (Nedungadi 1990; Hauser and Wernerfelt 1990; Roberts and Lattin 1991). Doing so allows us to distinguish between the effects of consideration and product utility on adoption, and estimate diffusion patterns that deviate from the stylized symmetric S-shape to which the conventional

Bass diffusion models are constrained. Consumers are waitlisted when insufficient retail inventory exists to satisfy demand (the shaded supply constraints structure in Figure 1). The waitlist itself may generate social exposure with either negative valence (dashed line and negative sign), or with positive valence (dashed line and positive sign), acting to weaken or strengthen the social contagion feedback. Clearing the waitlist requires that shipments out of inventory exceed new orders so as to work off the backlog. We describe the full model below, formalized as a system of nonlinear differential equations in continuous time.

FIGURE 1 ABOUT HERE

### ***Consumer Choice***

Consumers consider product adoption as a binomial choice between the conventional product  $c$  and a new product  $n$  in a saturated market. Consumers, currently using product  $i \in \{c, n\}$  decide to purchase product  $j \in \{c, n\}$  based on their affinity with each product,  $a_{ij}$  and  $a_{ii}$ . Therefore, market share  $\sigma_{ij} = \{\sigma_{cc}, \sigma_{cn}, \sigma_{nc}, \sigma_{nn}\}$  is:

$$(1) \quad \sigma_{ij} = \frac{a_{ij}}{a_{ii} + a_{ij}}$$

, with  $\sum_j \sigma_{ij} = 1 \forall i$ . Affinity  $a_{ij}$  multiplies a product utility-related component that is standard in discrete choice models,  $e^u$ , with consumers' willingness-to-consider a product,  $C$  (Struben and Sterman 2008).<sup>1,2</sup>

Willingness-to-consider a product captures the extent to which consumers are sufficiently familiar with the product so that they are willing to include it in their consideration set (Hauser and Wernerfelt 1990). Consideration is quantified as the fraction of the population willing to include the new product in their consideration set. We assume that consideration of the conventional product is full and stable for all consumers. Combined with the transitive nature of utility in Eq. 1, this allows us to treat  $c$  as an outside good with utility normalized to zero,  $a_{cc} = a_{nc} \equiv 1$ , an approach used commonly in logit models. Consumers already using the new product are similarly assumed to have full consideration of the new product, so  $a_{nn}$  only depends on the utility component  $e^u$ . Therefore only  $a_{cn}$  depends on consideration  $C$ :

$$(2) \quad a_{ij} = \begin{bmatrix} 1 & Ce^u \\ 1 & e^u \end{bmatrix}$$

The utility  $u$  of the new product  $n$  is a function of  $l$  product-specific attributes  $x_l$ :

<sup>1</sup> Assuming that the unobserved portion of utility  $\varepsilon$  is iid extreme value distributed across individuals, with  $u_h = u + \varepsilon_h$ , for individual  $h$ , the market share  $\sigma = e^u / (e^u + 1)$  (e.g. McFadden 1980; Train 2003). Implicitly, these studies assume fully informed consumers. However, affinity  $a = Ce^u$  can be restated as  $a = e^{u'}$ , with  $u' = u + \ln(C)$ . Thus, discrete choice properties are maintained for  $C \geq 0$ . Note that when consideration goes to zero, so does the likelihood of a product being in the consideration set.

<sup>2</sup> Other approaches are possible. For example, Thies, Kieckhäfer & Spengler (2016) use individual-based choice allowing that unobserved (latent) choice sets vary across the population (Ben-Akiva & Lerman 1985; Ben-Akiva & Boccara, 1995). Such an approach is useful when systemic variation exists in actor consideration of multiple-choice options. Our aggregate formulation is effective here given that it is simple, at the same level of aggregation as the rest of the model, consistent with classic discrete choice foundations, and does not require detailed individual-level data.

$$(3) \quad u = \sum_l \beta_l x_l + k$$

The attributes of the new product are defined relative to the conventional product, with each coefficient  $\beta_l$  reflecting the relative weight that consumers place on attribute  $l$ . The constant  $k$  captures any systematic (unobserved) differences between the alternative product and the set of conventional choices. Here we specify product attributes including price as exogenous, noting that an extensive literature exists on the determinants of prices, including product availability (e.g. Zettelmeyer et al. (2006) and Copeland et al. (2011)).

### ***Consumer Willingness-to-Consider***

Consumer willingness-to-consider a new product builds up over time as potential adopters learn about the product category (Nedungadi 1990; Hauser and Wernerfelt 1990; Roberts and Latin 1991). Consumer willingness-to-consider accumulates the impact of marketing and social exposure to the product from multiple sources. Formally, consideration  $C$  of the new product by consumers currently using the conventional product evolves as:

$$(4) \quad \frac{dC}{dt} = z(1-C)$$

where  $z$  is the sum of all sources of social exposure on consumers' willingness-to-consider the new product.  $C$  can be interpreted as the fraction of the population now using the conventional product who will include the new product in the consideration set for their next purchase.<sup>3</sup> The impact of social exposure is moderated by the term  $(1 - C)$ : As the fraction of the population

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<sup>3</sup> The full formulation accounts for the transfer of  $C$  associated with those drivers who switch platforms through a coflow formulation (Sternan 2000). See Struben and Sternan (2008)).

willing to consider the new product approaches 100%, the marginal impact of social exposure necessarily declines to zero.

Social exposure to the new product arises from different sources including advertising,  $z_m$ , word-of-mouth generated by adopters using the new product,  $z_s$ , and word-of-mouth from waitlisted buyers,  $z_w$ .

$$(5) \quad Z = Z_m + Z_s + Z_w$$

The socialization effect of advertising is a function of the level of advertising expenditure,  $z_m = f_m(m)$ , where  $f_m$  is a function capturing the potentially non-linear effect of advertising spending  $m$ . The socialization effect of word-of-mouth from adopters of the new product  $z_s$  is defined similarly, as a function of the proportion of adopters of new product,  $A_n$ , in the total population  $N$ ,  $z_s = f_s(A_n/N)$ . Finally, the socialization effect of the waitlist,  $z_w = f_w(L/N)$ , where  $L$  is the number of people currently waitlisted to purchase the new product. The effect of the waitlist may be positive or negative, and linear or non-linear with waitlist length, with the shape of any non-linearity being an empirical question.

### ***Supply Constraints***

The waitlist for product  $n$ ,  $L$ , increases with customer demand  $d$  and decreases with sales  $s$  and reneging  $g$ , if waitlisted customers become frustrated and cancel their order:

$$(6) \quad \frac{dL}{dt} = d - s - g$$

Reneging is assumed to occur at rate  $\lambda$ , so  $g = \lambda L$ .

Retailer inventory of product  $n$ ,  $I$ , increases with deliveries,  $y$ , and decreases with sales,  $s$ :

$$(7) \quad \frac{dI}{dt} = y - s$$

If inventory is available, customer orders are filled quickly, on average in the normal delivery delay,  $\tau_L$ , spanning the time required for activities such as order verification and processing, credit checks and arranging financing. If, however, product availability is low, sales are constrained by the stock of inventory and the interval,  $\tau_I$ , required to pick, pack and ship an item (in the automobile context, the time required to prep, inspect and register an in-stock vehicle, then schedule and complete delivery to the customer). Thus, retail sales are the lesser of the desired delivery rate given the number of customers seeking the product and the maximum delivery rate possible given the inventory on hand, consistent with Little's Law (Little 1961):

$$(8) \quad s = \text{MIN} \left( \frac{L}{\tau_L}, \frac{I}{\tau_I} \right)$$

The second term on the right hand-side of Eq. (8) ensures that inventory remains non-negative even if there is strong demand.

### ***Installed Base***

Sales of durable goods depend on both initial and replacement purchases, so the dynamics of the installed base must be considered (Olson and Choi 1985; Norton and Bass 1987). The growth and turnover of the installed base also play an important role in the evolution of consumer willingness-to-consider a product and demand in the population of non-adopters, governing the rate of vehicle replacements in the fleet, and hence demand for new vehicles.

We capture the product installed base using a standard multiple-vintage cohort model (Sterman 2000, Ch. 12) of automobiles (Greenspan and Cohen, 1999), with vintage-specific discards and replacement purchases, allowing for total market size adjustments. A product's indicated discards absent market size adjustments,  $o_{iv}$ , increase with normal the hazard probability  $h_v$  (defined during the cohort time  $\tau$ ; generally increasing in vintage  $v$ ), and cohort installed base  $A_{iv}$ ,  $o_{iv} = h_v A_{iv}/\tau$ . Adjusted discards,  $o'_{iv}$ , account for a market contraction fraction  $k^-$ , equal to the relative gap between the actual installed base  $A$  and (lower) indicated installed base, with adjustment time  $\tau_a$ . Then  $o'_{iv} = h_v A_{iv} \left[ (1 - k^-) / \tau + k^- / \tau_a \right]$  and total replacements for product  $i$ ,  $r_i = (1 - k^-) \sum_v h_v A_{iv} / \tau$ . Demand for a product  $j$ ,  $d_j$ , derives from market shares  $\tilde{A}_{ij}$  from replacements across all products  $r_i$  as well as from a market expansion correction proportional to  $k^+$ , the relative gap between the actual and (higher) indicated installed base, and market share  $\sigma_{jj}$ . Thus,  $d_j = \sum_i \sigma_{ij} r_i + \sigma_{jj} k^+ / \tau_a$ . Finally, the total installed base for the new product ( $i=n$ ),  $A_n$ , is the sum of the new product's installed base cohorts,  $A_n = \sum_v A_{nv}$ .

## The Diffusion of the Toyota Prius Hybrid-Electric Vehicle

The Toyota Prius hybrid-electric vehicle was introduced in the US in July 2000, one of the first hybrid electric vehicles available to consumers. Distinctively styled, and achieving significantly better fuel economy than conventional gasoline vehicles, the Prius quickly developed a

reputation as an icon of green motoring, desired by environmentally conscious consumers and celebrities in particular (Yeatman 2007). Sales of the Prius grew steadily in the US through the mid-2000s after the larger 2<sup>nd</sup> generation Prius was introduced in 2003, before plateauing in 2008 (Figure 2). Today the Prius remains the dominant hybrid-electric vehicle model in the US, and accounts for more than 50% of all hybrid sales to date.

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FIGURE 2 ABOUT HERE

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However, sales data give an incomplete picture of demand for the Toyota Prius in the United States, because sales were at times limited by product availability, resulting in the lengthy waitlists that we study in this paper. All Prius vehicles sold in the US to this day are imported, and various constraints have limited the supply of Prius vehicles available to US buyers over time, including: surging global demand, limited product capacity of nickel metal hydride battery packs manufactured for the Prius by Panasonic EV Energy (Soble and Simon 2008), a Prius safety recall in early 2010, and the Japan tsunami in March 2011. Data on Prius waitlists are not readily available, a situation that is common for most products. Firms frequently lack systematic waitlist data, because placing one's name on a waitlist often does not generate a transaction that is captured by point-of-sale systems. In the case of the Prius, each Toyota dealership managed its own Prius inventory and waitlist. To overcome this barrier, we assembled a unique dataset measuring national average Prius waitlists using multiple data sources. We compiled references



to Prius waitlists in all major US newspapers from 2000 to 2009 inclusive, and also obtained order databases from the Prius enthusiast websites HybridCars.com and PriusChat.com. We then (1) manually identified all references to the current length of the Prius waitlist in the articles; (2) recorded the frequency of references to Prius waitlists by month and (3) tabulated waitlist lengths from the two websites (A detailed description of the data collection process is provided in the Supplementary Information). While collection of data from media reports has the potential for measurement error due to omissions, we have no evidence to suggest any systematic bias exists. The monthly estimates of Prius waitlist length (Figure 3) are in broad agreement with the frequency of references to Prius waitlists ( $r = 0.673$ ,  $p < 0.000$ ) and with the website data. Waitlist lengths can be reasonably expected to be similar across Toyota dealerships, because consumers search for their desired vehicle across multiple dealerships, and because dealers trade vehicles to match vehicles with buyers. The data reveal sustained and lengthy waitlists from 2004-2007, with two smaller waitlist outbreaks around 2001 and 2008.

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FIGURE 3 ABOUT HERE

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To demonstrate the importance of our waitlist data, Figure 3 compares our estimate of Prius waitlists with two measures of inventory coverage: (1) overall US Prius inventory coverage (including vehicles on dealer lots, vehicles in transit to dealerships and Prius vehicles that have

cleared customs awaiting delivery) for 2000-2009, obtained from Wards; and (2) the average inventory coverage of Toyota dealerships (only vehicles on dealer lots) for 2005-2009, obtained from JD Power. These two measures of inventory coverage are highly correlated ( $R^2 = 0.894$ ). Fluctuations in dealer inventory coverage lag and have smaller magnitude than the national coverage data because dealer inventory does not account for Prius vehicles that have landed in the US but have not yet been delivered to a dealership. To quantify the relationship between the two measures of inventory coverage we estimate dealer inventory coverage ( $DIC$ ) as a lagged function of Toyota's national inventory coverage ( $NIC$ ):  $DIC = \alpha + \beta NIC_{t+\lambda}$ , yielding  $\alpha = -0.246$  (95% confidence interval: -0.536, 0.035),  $\beta = 0.617$  (0.607, 0.627) and  $\lambda = 2.368$  months (2.316, 2.434). That is, dealer inventory coverage lags the national coverage data by 2.4 months. Figure 3 further shows that dealer inventory coverage is out of phase with the length of the waitlist ( $r = -0.310$ ,  $p < 0.000$ ).<sup>4</sup> This relationship is expected: when inventory coverage is high, e.g. July 2002 - Jan 2004, waitlists are zero because inventory is available to satisfy all prospective Prius buyers. Crucially, however, inventory coverage is not a sufficient statistic for waitlist length, because inventory coverage cannot fall below zero.<sup>5</sup> Thus, inventory coverage and waitlist length are not well-correlated. While a formal proof is provided in the Supplementary Information, the graph illustrates the importance of waitlist data in the case of the Prius: While inventory coverage is at its minimum from January 2005 through October 2006, the

<sup>4</sup> Calculated using actual dealer inventory coverage for 2005-2009 and simulated dealer inventory coverage for 2000-2004.

<sup>5</sup> In practice, inventory coverage does not reach zero even when the waitlist is very large because there is some minimum time between the delivery of a vehicle to a dealer and the delivery to the customer. That time consists of the minimum time required to prep and register the vehicle, and to finalize the purchase with the customer.

waitlist begins low, builds to a high level, then shrinks again. The length of the Prius waitlist therefore provides important information that is not captured in inventory coverage data.

## Model Estimation

Our aims in estimating model parameters are to: (i) test the ability of the model to replicate the observed Prius sales and waitlist dynamics, (ii) identify the effect of waitlists on social exposure, and (iii) identify potential biases in estimated parameters in diffusion models caused by omission of supply constraints and waitlists. Necessarily, various structural and parametric assumptions are needed to apply the generalized model to the Prius case, which we summarize in Table 1. Further details of our operationalization and data sources are provided in the Supplementary Information.

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TABLE 1 ABOUT HERE

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We use maximum likelihood estimation (MLE) as suggested by Schmittlein and Mahajan (1982) to estimate diffusion model parameters for social exposure and utility. The logit choice likelihood function is defined as:

$$LL(\theta|\varepsilon_{ts}; \varepsilon_{tw}) = -\frac{T\ln(2\pi)}{2} - \sum_{t=1}^T \left[ (\ln(\sigma_s) + \ln(\sigma_w)) - \left( \frac{\varepsilon_{ts}^2}{2\sigma_s^2} + \frac{\varepsilon_{tw}^2}{2\sigma_w^2} \right) \right] \quad (9)$$

where  $\theta$  is the set of parameter values,  $e_{ts}$  ( $e_{tw}$ ) are the estimation errors at time  $t$  (given  $\theta$ ) for respectively sales and waitlist, and  $\sigma_s$  ( $\sigma_w$ ) the standard deviation of the estimation error, respectively, over the estimation period 1 to  $T$ . The likelihood function includes both sales and waitlist, each weighted by the inverse of their standard deviation of residuals (Eliason 1993), determined by iterative model fitting. We use Markov Chain Monte Carlo (MCMC) simulation (Geyer 1992) applied to the likelihood landscape to estimate confidence intervals, because estimation of the confidence intervals using the complete multivariate likelihood surface is computationally prohibitive, while asymptotic methods based on the curvature of the likelihood function at the point estimate may be biased (Struben et al. 2014).

## Results

We estimate six alternative models, beginning with a demand-side model in which there are no capacity constraints or waitlists, then gradually relax limiting assumptions to build up to the full supply constraints model. We first consider four counter-factual models that exclude supply constraints and waitlists, to understand the extent to which a model without supply constraints is able to replicate the dynamics observed in the Prius case (Demand Model 1 only includes social exposure to marketing and word-of-mouth from Prius adopters with constant product utility;

Demand Model 2 includes the effect of inventory coverage in the utility function, Demand Model 3 includes the effect of waitlisted buyers (exogenously specified) as a source of social exposure, and Demand Model 4 considers both effects). In these demand-only models we assume that inventory is always available to fulfill customer demand, so  $s = L/\tau_L$  (Eq.8) and Eq.7 is not used. We then estimate two models with the full supply constraints structure, quantifying the effect of unsatisfied demand on parameter estimates. Supply Constraints Model 1 includes social exposure from marketing, word-of-mouth, and an endogenously generated waitlist. Supply Constraints Model 2 includes total cost of ownership in the utility function to test the robustness of the socialization parameter estimates when controlling for key product attributes. Table 2 summarizes how the models differ in terms of structure and estimated parameters (All other parameters take identical values across all models.)

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TABLE 2 ABOUT HERE

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Table 3 shows the parameter estimates for each model. In Demand Model 1, the parameters for advertising and driver word-of-mouth are positive and statistically significant, with relative magnitudes broadly consistent with the average value of 0.03 for  $e_m$  and an average value of 0.38 for  $e_s$  found across empirical applications of the Bass model (Sultan et al. 1990).

Demand Model 2 adds inventory coverage as a measure of product availability affecting consumer choice, consistent with earlier approaches (Balachander et al. 2009). The inventory coverage coefficient is not statistically significant, and its impact on the advertising and socialization coefficients and model fit is negligible. In contrast, Demand Model 3 introduces social exposure from waitlisted Prius buyers. The waitlist is highly statistically significant, and the model performs much better than either Demand Model 1 or 2 (LL=1,093 vs 1,105, test statistic  $G_{df=2} \sim \chi^2_{df=2} = 24$ ,  $p < 0.001$ , where  $df$  is the degrees of freedom of  $G$  and  $\chi$ ). In addition, the inclusion of waitlist socialization in Demand Model 3 leads to a significant reduction in the Theil bias ( $U^m$ ) and unequal variance ( $U^s$ ) coefficients, indicating that the model better captures the mean and variance in the data respectively. Comparing the behavior of Demand Model 1 and Demand Model 3 (Figure 4), it can be observed that Demand Model 3 is better able to simulate the volatility in sales in the period 2005-2008, although both models still miss important low-frequency variation in sales. Further, neither model is able to simulate the observed waitlist behavior in the absence of structure representing product availability.

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TABLE 3 ABOUT HERE

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#### FIGURE 4 ABOUT HERE

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Earlier we noted that the valence of social exposure from the waitlist could be positive or negative. Here we find a positive coefficient, consistent with the hypothesis that waitlisting provides social proof and status signaling. The magnitude of social exposure generated by a waitlisted buyer is substantially greater than that of a Prius owner (9.28 vs 0.27), which is unlikely to be explained by word-of-mouth from individual waitlisted Prius buyers alone. We hypothesize that media coverage of Prius waitlists may amplify social exposure, an effect found in other contexts such as elections (Ridout et al. 2008). Media attention may be expected to be even less sensitive to changes in waitlist length than word-of-mouth from waiting buyers. We note also that the marketing and word-of-mouth coefficients in Demand Model 3 are significantly lower than in Demand Model 2, suggesting that omitting the impact of waitlists leads to estimation bias.

As a further test of the importance of the waitlist, Demand Model 4 adds Prius inventory coverage to Model 3. As in Demand Model 2, the inventory coefficient is not statistically significant, and its inclusion does not result in a statistically significant improvement in model fit. These results show (1) the impact of waitlists cannot be proxied by supply-side metrics such as inventory coverage, and (2) waitlists appear to have a substantial positive impact on Prius adoption.

We now estimate the full Supply Constraints model in which the waitlist is endogenously generated through the interaction of demand and product availability (Eqs. 6-8). Supply Constraints Model 1 extends Demand Model 3, with waitlist length now endogenous, and the model calibrated to both sales and the waitlist. We first consider a linear effect of waitlist length on social exposure ( $e_w$ ). The results are qualitatively the same as in Demand Model 3, building support for the argument that effectively measuring and capturing the influence of waitlists is critical. However, the model with endogenous supply constraints yields important improvements over the demand-side model. First, the Supply Constraints model explains the origin and length of the waitlist from the interaction of socialization and consideration with product availability. Second, the Supply Constraints model is better able to capture the peaks and troughs in observed sales, reducing the Theil unequal variance fraction ( $U^s$ ) by 66%. Finally, the difference between the estimated impact of advertising in Demand Model 3 and Supply Constraints Model 1 is large and highly statistically significant ( $p < 0.001$ ), again showing that omitting supply constraints in diffusion models may lead to biased parameter estimates, consistent with the theoretical argument of Ho et al. (2002). (The waitlist socialization effect is smaller in Supply Constraints Model 1 than in Demand Model 3, but the difference is not statistically significant ( $p = 0.12$ ).) Figure 4 shows that Supply Constraints Model 1 closely replicates the observed sales trend, while also capturing the overall trend in the waitlist. Although some variation in peak waitlist lengths exists, the Supply Constraints Model effectively explains both sales and the extent of surplus demand over time, resulting in part from the accumulation of social influence from



multiple channels including waitlisted buyers. One explanation for differences in fit may be the introduction of the 3<sup>rd</sup> generation Toyota Prius in 2009 (beyond the scope of our model), and by measurement noise in our waitlist data.

We introduce the effect of total cost of ownership on utility in Supply Constraints Model 2. We do not find a statistically significant relationship between *tco* and utility, although this is not surprising given the limited variation in the determinants of *tco* in our dataset. Variation in the price of the Prius relative to conventional vehicles is small: federal incentives were only available for a short period (Supplementary Information) and, although incentives varied widely across states (Gallagher and Muehlegger 2011), the magnitude of state-level financial incentives was modest in most cases. While dealers vary their margins, as Sallee (2006) points out, the resulting variation in prices is a small fraction of the vehicle price. Similarly, although gasoline prices varied substantially over the time horizon, operating costs for both the Prius and conventional vehicles are highly correlated, differing only to the extent that Prius fuel economy exceeds that of the conventional vehicle.

In the above models we assume that the impact of waitlists on social influence is linear, a reasonable first-order approximation of a potentially nonlinear underlying relationship. However, sufficiently long waitlists most eventually increase customer frustration, offsetting the positive socialization benefits found in the estimation results, and, for sufficiently long wait times, causing the net valence of the waitlist influence to become negative. In Supply Constraints Model 3 we test whether this frustration effect is observed in the Prius case. We estimate the

non-linear effect of waitlist length on social exposure with a second waitlist socialization term, proportional to the square of the probability of contact with a waitlisted Prius buyer. If the longest waitlists for the Prius caused customers to become frustrated, the second-order term would be negative. However, we are unable to find a statistically significant non-linearity in waitlist influence here, with MCMC confidence interval estimates hitting the wide user-imposed bounds on the parameter estimation space. The results suggest that the waitlist was not sufficiently long in the Prius case for any frustration effect to be significant, or that our aggregate waitlist data lacks sufficient granularity to estimate any non-linear effect of waitlists.

The behavior of Supply Constraints Model 2 during the estimation period highlights the ability of the model to explain diffusion dynamics which classic diffusion models that omit supply constraints and the impact of waitlists cannot. Figure 5 illustrates with further detail the behavior for Supply Constraints Model 2. Sales growth (Figure 5a) is enabled by the gradual buildup of consumer willingness-to-consider (Figure 5b), consistent with observations that consideration for various product categories has remained low despite initial sales success (Roberts and Lattin 1991; Erdem and Swait 2004). The model effectively accounts for the unsatisfied demand of waitlisted Prius consumers (Figure 5c), a process ignored by traditional diffusion models. The sources of consideration growth (Figure 5d) show the impact of advertising is highest when the product is first launched, and when advertising jumps with the introduction of each new Prius generation, while social exposure arising from Prius drivers builds slowly and steadily. The socialization effect of the waitlist occurs during times of shortage

(2004-2008), accounting for close to one-third of the cumulative social exposure through the end of 2009.

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FIGURE 5 ABOUT HERE  
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As a further test of the model, we simulate beyond the estimation period using actual gasoline prices and light duty vehicle sales. The out-of-sample simulation is counterfactual, as dramatic market changes occurred in the period from 2010-2014, including: extensive safety recalls of Toyota vehicles between December 2009 and February 2010, the 2011 Japan tsunami disaster, which suppressed Toyota production that year, and increasing availability of other HEV models, including larger and smaller Prius variants and HEVs from other automakers (Figure 5a). In contrast, the out-of-sample simulation omits the impact of the recalls and tsunami, and assumes that Prius advertising continues at historical average levels, that no new Prius variants are introduced, and, most importantly, that there is no entry of HEVs from other auto OEMs. Under those conditions, Prius sales would have grown substantially as the accumulation of social exposure continued to build consideration (Figure 5d). Simulated sales are close to, but somewhat lower than, actual sales of all HEV models in the US, providing an approximate

estimate of how much the entry of competing HEVs, the 2011 Tsunami and recalls suppressed actual Prius sales after 2010.

## Discussion

Waitlists during the launch of new products are common, yet the innovation diffusion literature has largely ignored the role of supply constraints, and of waitlists in particular. We offer a new theory of how supply constraints condition the diffusion of new durable products in multiple ways. Most obviously, supply constraints limit sales when demand exceeds supply. However, the existence of unsatisfied demand can also generate substantial social exposure, directly from waitlisted customers and indirectly through media attention. Thus, the interaction of supply constraints with social exposure not only affects current demand, but also conditions future demand and the overall pattern of diffusion. The strength and valence of social exposure generated by waitlists – affecting the polarity of the feedback loop involving the effect of waitlists on social exposure – is likely to depend on the context, including the nature of the product and the nature of the shortage, reflecting how customers and media respond to the shortage.

Our model allows consideration of how strategic decisions on the supply side (i.e. capacity management) and demand side (i.e. pricing and advertising) interact. Coordinating marketing, pricing and capacity for new products is a major challenge for managers seeking to satisfy consumer demand while avoiding the risks of costly overcapacity. Policies that use product scarcity as a strategic lever (Wind and Mahajan 1997; Stock and Balachander 2005;

Balachander and Stock 2009) may be even more effective if media attention can be generated for hot products, as was the case with the rollout of Tesla's long-awaited Model 3 electric vehicle (Vlasic 2017).

Our analysis of the Prius case provides strong empirical support for the hypothesis of Ho et al. (2002) that omitting supply constraints may lead to substantively large and statistically significant bias in estimates of diffusion model parameters. Further, we show that inventory coverage is a problematic proxy for waitlist data. Because waitlist data are usually difficult to obtain, empirical analysis usually relies on proxies such as inventory coverage. To overcome this barrier, we assembled a unique dataset measuring national average Prius waitlists using multiple data sources. In showing how effective estimation depends on both model structure and access to appropriate data, we demonstrate the importance of leveraging intermediate-level data that captures the variables of greatest concern to decision-makers. For managers, omitting waitlists from diffusion models may lead to overestimation of the impact of advertising and classic adopter-generated word-of-mouth compared to the impact of waitlists, resulting in misleading and potentially harmful policy advice regarding the impact of decisions that might be undertaken by firms (e.g., marketing, pricing, availability) and governments (e.g., incentives, subsidies).

While the history of the Toyota Prius is an excellent case to study the diffusion of durable goods under supply constraints, our approach has limitations. First, the data are necessarily limited to the early stage of the new product lifecycle: at the end of 2014 the market share of all hybrid vehicles in the US was little more than 3%, with Prius sales far from saturating, meaning

that identification of product potential separately from the overall strength of social exposure is not possible. While uncertainty about product potential does not affect the relative strength of the three exposure parameters, subsequent research on full product life cycles could provide additional clarity about their absolute strength. Second, as is common in new product diffusion models, it is impossible to fully control for potential endogeneity in estimates due to codetermination in and potential omission of variables. Endogeneity is a persistent challenge in diffusion models relying on non-experimental data or imperfect natural experiments because individuals are not assigned randomly to different conditions, e.g. random assignment to social exposure versus no social exposure, waitlist versus no waitlist, etc. (Zettelmeyer et al. 2006). In our case, dealer prices and demand interact as dealer prices are high precisely during periods of high demand—and long waitlists. While our estimates of demand could therefore be biased even though we incorporated dealer discount data in the models, prior analysis of the effect of waitlist on dealer markups suggests that the impact of dealer response on demand is limited (Sallee 2006). Although in principle it is not possible to rule out all possible omitted variables, we have considered a wide range of variables that could theoretically explain the waitlist dynamics by providing exogenous shocks to demand, including changes in the availability of other hybrid vehicles, awards won by the Prius for quality or other positive media attention, changes in societal attitudes towards sustainability and climate change, and geopolitical events regarding oil and energy security. We are yet to find any data showing that these alternative explanations are correlated with the distinct waitlist pattern observed.

Despite endogeneity issues in the estimation of diffusion models, they remain valuable and are widely used in both theory and practice. Managers must make capacity decisions with limited data and before sales peak, and typically cannot carry out experiments to address identification and endogeneity issues. Applying the model to other cases with greater variation in variables may allow more accurate estimation of the relative importance of competing social exposure channels, mechanisms such as reneging, and the relative importance of waitlist length versus waiting time, including potential nonlinearities. This may be achieved through spatial disaggregation, inclusion of multiple products, or considering cases with longer time horizons that span more of the full product lifecycle. Finally, in applying our model to different empirical cases, we can better understand the context-specific nature of strategy and policy-making in the presence of supply constraints and waitlists.

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## Tables and Figures

Table 1: Model Estimation Overview

Sub-Model	Approach
Time Horizon	We estimate the model for the case of the Toyota Prius in the US from June 2000, its first introduction in the United States, to December 2009 inclusive.
Consumer Choice	We model consumer choice (Eq. 1) between the Prius and a comparable popular gasoline vehicle from the market segment in which the Prius competes. For the first generation Prius, a compact car, we select the Toyota Corolla hatchback. For the second and third generation Prius, a midsize car, we select the Toyota Camry. By selecting these Toyota models, we also eliminate issues relating to the differential impact of brand attributes such as reputation and customer brand loyalty.
Utility Attributes	<p>While estimating attribute sensitivities is not our primary aim, we consider the following key vehicle attributes conditioning product utility (Eq. 3) in the estimation to avoid potential unobserved variable biases:</p> <ul style="list-style-type: none"> <li>• Total cost of ownership <i>tco</i>: the purchase price plus the present value of lifetime operating costs (measured in \$'000), assuming 12,000 miles/year driving for 10 years given current gasoline prices and a 4% discount rate, taking the difference between the Prius and the comparable gasoline vehicle.</li> <li>• Inventory coverage <i>incov</i>: a demand-side measure of Prius inventory availability (measured in months). While waitlists may influence demand through social exposure – from prospective buyers or through media attention - we include inventory coverage as a utility attribute, providing an alternative explanation of the role of waitlists. This distinction is behaviourally appropriate, as inventory coverage signals to potential buyers vehicle availability at dealerships, affecting directly the appeal of the product among those already considering a vehicle.</li> <li>• Prius-specific constant <i>k</i>: capturing the influence of unobserved characteristics of the Prius (such as performance, aesthetics, and conferred social status) as well as the difference in the variety of makes, models and options available for the Prius compared to conventional vehicles that remain. We set <math>k = -1</math> for all the models we estimate in the paper, implying a Prius market share potential of 27% within its market segment if full consideration were to be reached. In the Supplementary Information we demonstrate using formal arguments and sensitivity analysis that our main results are robust to different values of <i>k</i>.</li> </ul>
Social Exposure	<p>We assume that the influence of marketing and word-of-mouth from adopters on consideration is linear (Eq.5, <math>z_m</math> and <math>z_s</math>), in the absence of data suggesting otherwise. This approach is common in marketing diffusion models, particularly especially when new products have low market shares (Bass 1969, Vakratsas et al. 2004). We therefore estimate <math>z_m = e_m m</math> and <math>z_s = e_s A/N</math>, where <math>e_m</math> is the effectiveness of marketing spending (per \$M), and <math>e_s</math> is the strength of word-of-mouth.</p> <p>While marketing and word-of-mouth effects tend to be positive, the effect of the waitlist (<math>z_w</math>) could be positive or negative, and changing, depending on whether the waitlist provides social status and generates excitement and media attention that outweighs any frustration generated by long wait times. We therefore first formulated the effect of waitlist word-of-mouth as <math>z_w = e_w L/N + e_w^2 (L/N)^2</math> to capture these possibilities, positive and negative.</p>
Reneging	We omit the potential for reneging in the models we estimate ( $\lambda = 0$ ), since we did not find evidence of reneging in our dataset, and we have no other evidence to suggest that reneging was a significant influence in the Prius case. (This assumption is unlikely to change our qualitative findings even if some reneging existed.)
Other Model	We assume the average delivery time $\bar{A}$ and average waitlist recall time $\bar{A}$ (Eq. 8) to both be 0.1 months (3 days) based on discussions with US car dealers. We

Parameters	represent 2 cohorts in the installed base cohort model.
Estimation Data	We use direct measures where available (e.g. sales advertising spending) and indirect measures where they are not. In the case of waitlist length (Eq 6), we triangulate Prius waitlist length data from multiple sources, and calculate the number of buyers on the waitlist as waitlist length * monthly sales rate. Indirect measures include deliveries of Prius vehicles to Toyota dealerships, $y$ , (Eq. 7), calculated for 2005-2009 using the dealer inventory coverage data we obtained from JD Power.

Table 2: Comparison of Estimated Models

Model Component	Model Equation	Demand Model 1	Demand Model 2	Demand Model 3	Demand Model 4	Supply Constraints Model 1	Supply Constraints Model 2	Supply Constraints Model 3
Endogenous Supply Constraints?	(6)-(8)	No	No	No	No	Yes	Yes	Yes
Utility Function	(3)	$u = k$	$u = \beta_2 invcov + k$	$u = k$	$u = \beta_2 invcov + k$	$u = k$	$u = \beta_1 tco + k$	$u = \beta_1 tco + k$
Socialization from Marketing?	(5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Influence from Adopters?	(5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social Influence from Waitlisted Buyers?	(5)	No	No	Linear (Exogenous)	Linear (Exogenous)	Linear (Endogenous)	Linear (Endogenous)	Quadratic (Endogenous)

Table 3: Model Parameter Estimates

Parameter	Demand Model 1	Demand Model 2	Demand Model 3	Demand Model 4	Supply Constraints Model 1	Supply Constraints Model 2	Supply Constraints Model 3
Advertising Effectiveness ( $e_m$ )	0.242*** (0.201, 0.283)	0.242*** (0.203, 0.291)	0.110*** (0.047, 0.174)	0.109*** (0.045, 0.167)	0.203*** (0.197, 0.210)	0.191*** (0.069, 0.252)	0.190*** (0.003, 0.751)
Effective Contact Rate: Prius Drivers ( $e_s$ )	0.674*** (0.495, 0.878)	0.673*** (0.488, 0.881)	0.272*** (0.067, 0.480)	0.230** (0.003, 0.451)	0.275*** (0.128, 0.387)	0.279*** (0.095, 0.668)	0.279*** (0.153, 0.742)
Effective Contact Rate: Waitlisted Buyers ( $e_w$ ) - Exogenous	-	-	9.280*** (6.319, 12.224)	9.274*** (6.499, 12.496)	-	-	7.241 (1.573, 20^)
Effective Contact Rate: Waitlisted Buyers ( $e_w$ ) - Endogenous	-	-	-	-	6.402*** (4.618, 9.004)	7.241** (0.641, 19.180)	-
Effective Contact Rate: Waitlisted Buyers <sup>2</sup> ( $e_{w^2}$ ) - Endogenous	-	-	-	-	-	-	0.027 (-1,000^, 1,000^)
Total Cost of Ownership ( $^2$ $l$ )	-	-	-	-	-	0.010 (-0.039, 0.145)	0.010 (-0.046, 0.136)
Inventory Coverage ( $^2$ $z$ )	-	4.54E-5 (-0.005, 0.004)	-	0.002 (-0.003, 0.005)	-	-	-
Log-Likelihood	-1105.30	-1105.30	-1093.04	-1092.59	-2256.84	-2256.4	-2256.4
R <sup>2</sup> – Sales	0.855	0.855	0.875	0.873	0.953	0.954	0.954
Theil Bias Fraction ( $U^m$ ) - Sales	0.011	0.011	0.001	0.001	0.001	0.001	0.001
Theil Unequal Variance Fraction ( $U^s$ ) - Sales	0.135	0.135	0.049	0.053	0.018	0.018	0.018
Theil Unequal Covariance Fraction ( $U^c$ ) - Sales	0.854	0.853	0.951	0.946	0.982	0.981	0.981
R <sup>2</sup> – Waitlist	-	-	-	-	0.264	0.268	0.268
Theil Bias Fraction ( $U^m$ ) - Waitlist	-	-	-	-	0.018	0.019	0.019
Theil Unequal Variance Fraction ( $U^s$ ) - Waitlist	-	-	-	-	0.066	0.074	0.074
Theil Unequal Covariance Fraction ( $U^c$ ) - Waitlist	-	-	-	-	0.916	0.907	0.907

(lower, upper) = 95% confidence interval. \*\*\* = significant at  $p \leq 0.01$ . \*\* = significant at  $p \leq 0.05$   
^ Optimization reached user-defined bound on parameter space

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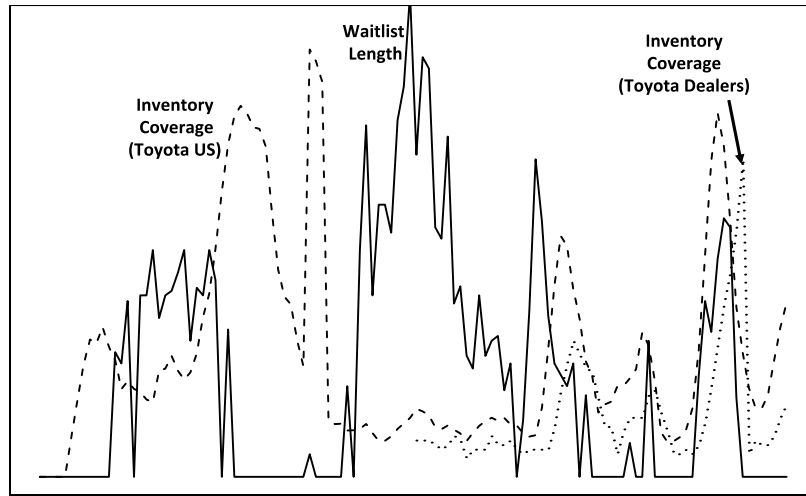


Figure 3: Comparison of Toyota Prius inventory coverage and waitlist length estimates. Sources: Toyota Inventory: Wards; Dealer Inventory: J.D. Power; Waitlist: Assembled from multiple sources (See Supplementary Information for details)

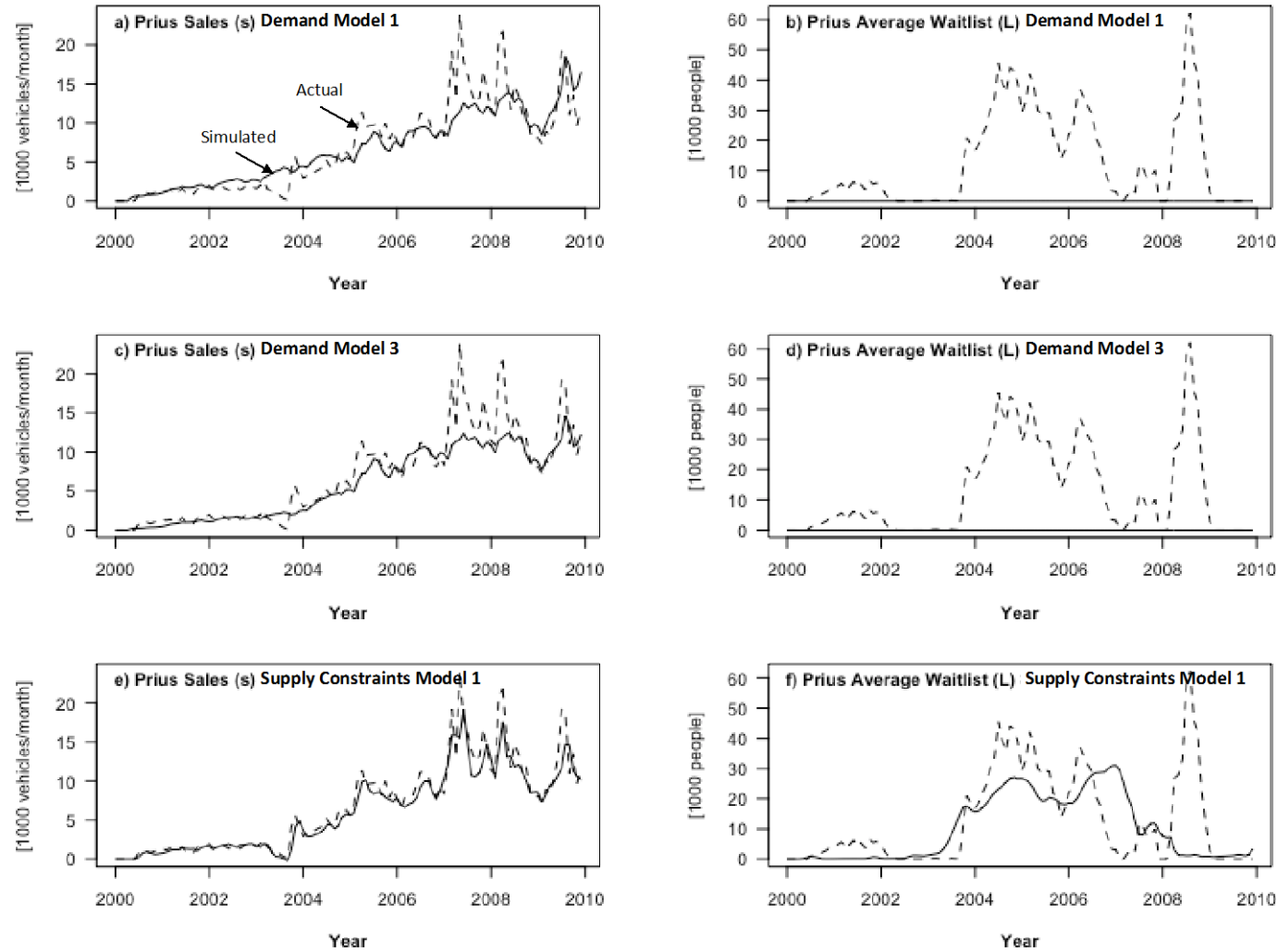


Figure 4: Comparison of Model Simulations



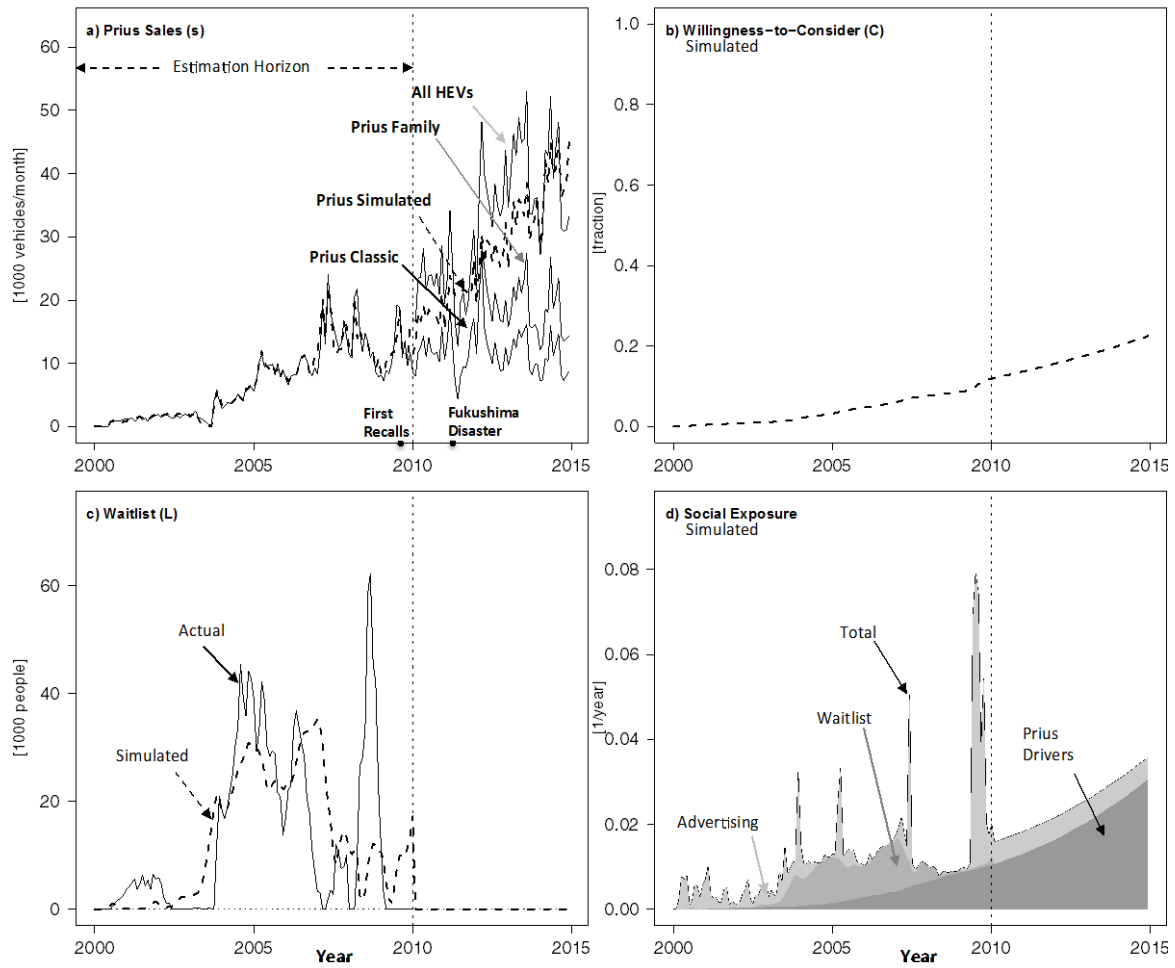


Figure 5: Simulation of market share, willingness-to-consider, waitlist, and social exposure.

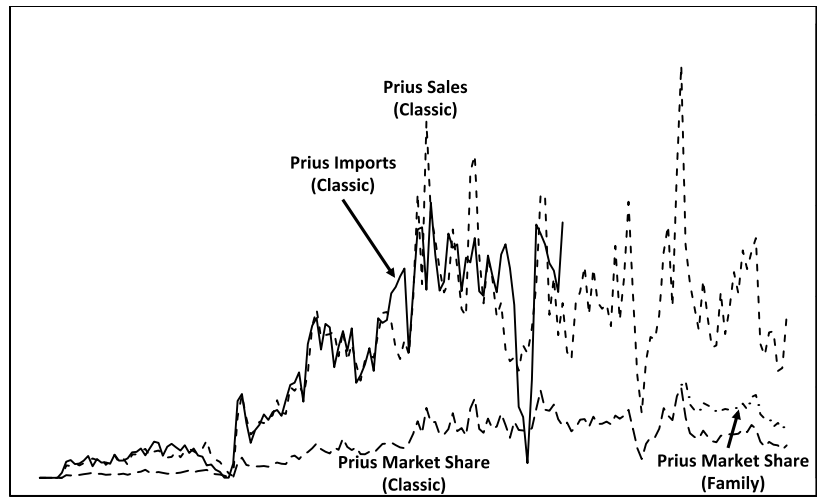


Figure 2: Toyota Prius US monthly imports and sales; share of total light vehicle sales (2000-2014). Sources: Automotive News (2014), Fourin (2010), Toyota (2011).

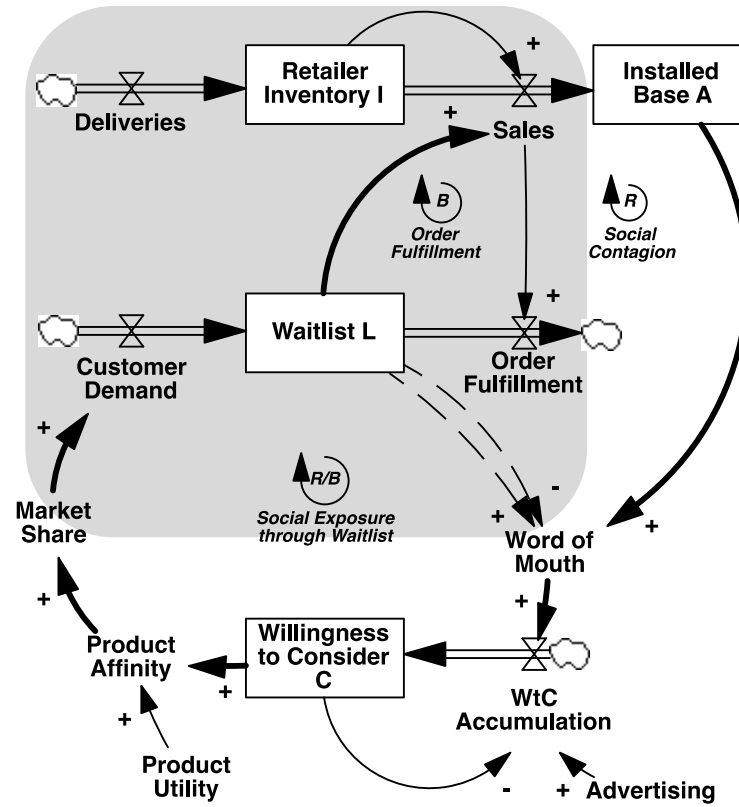


Figure 1: Causal structure of the model